Life-Cycle Demand for Major League Baseball

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Abstract

Static microeconomic theory predicts that monopolists would set prices in the elastic range of demand. For nearly thirty years, a recurrent empirical finding on sports attendance demand however has not supported this prediction. This paper shows that in a multiple time-periods model, professional team owners are likely to set inelastic prices, if the intertemporal elasticity of substitution for games is small, and/or if attending games is habit-forming. Our empirical study shows that these two conditions hold for the Major League Baseball (MLB) attendance. This result supports the notion that inelastic pricing would be the outcome of MLB owners' rational decisions.

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1. Introduction

Professional sports teams have monopolistic powers over their local sports markets. Basic microeconomic theory predicts that a monopolist maximizes her profits by choosing the output level at which marginal revenue (MR) equals marginal cost (MC).[1] This profit maximization condition implies that the owner of a professional sports team will set the ticket prices in the inelastic region of the attendance demand. However, the previous empirical studies of the sports attendance demand have almost uniformly found that the owners of professional sports teams do not set ticket prices in the elastic regions of the gate demand. There is a long list of the studies that report statistically insignificant and/or inelastic price-elasticity of attendance (for example, Noll, 1974; Siegfried and Eisenberg, 1980; Jennett, 1984; Scully, 1989; Welki and Zlatoper, 1994; Coffin, 1996; Fort and Rosenman, 1999a, 1999b; and Lee, 2006). We can find broad reviews on this literature from Fort (2004) and Krautmann and Hadley (2006).

An alternative explanation of these seemingly contradictive empirical findings has been offered in the literature. Fort (2003) and Krautmann and Berri (2006) observe the ticket price to be only a part of the total costs that a person should bear to attend a game.

[1] This result also holds for the producers of differentiable goods in imperfectly competitive markets. In fact, the theories we discuss below do not require the owners of sports teams to be pure monopolists. They only require the owners to have some monopolistic power to control the ticket prices for their teams' home games. However, for expository convenience, we will assume throughout the paper that the owners are (local) monopolists.

Based on this observation, they argue that the ticket-price elasticity of attendance may be low while its total-cost elasticity is greater than one. This would be the case, especially when the owners can compensate their revenue losses from ticket sales by the revenue gains from parking, concessions and merchandise sales. Extending these studies, Fort (2004) examines the profit maximization problem of a team owner with two revenue sources (local television broadcasting and attendance) that has been also considered by Fort and Quirk (1995) for other contexts. Specifically, Fort considers a model in which teams choose the levels of the players' talent to produce the wins which can be sold both at the gate and on television. In this model, a team owner maximizes his/her profits at the level of the talent at which the marginal revenue from the gate attendance equals a weighted sum of three measures: the marginal cost of hiring an additional playing talent, the marginal revenue from local TV broadcasting, and the average of the other teams' marginal revenues from TV broadcasting in the same league. From this optimization condition, Fort finds that a team sets ticket price in the inelastic attendance-demand region, if the team's marginal revenue from broadcasting is "large enough" relative to the averages of the other teams.

However, the results of Fort (2004) do not fully explain the puzzle of inelastic pricing in the sports where the revenues from local TV broadcastings are negligible, such as National Football League (NFL). Furthermore, the empirical regression analyses using the total costs of attendance (including travel and/or other opportunity costs) instead of ticket prices still yield inelastic estimates (Bird, 1982; Fort and Roseman, 1999a, 1999b).

This paper provides an alternative theory for the inelastic pricing in the professional sports market. This paper makes two contributions to the literature of sports economics. First, we show that if the sports fans' consumption decisions are forward-looking, that is, if the fans decide their attendance consumption levels based on their real life-cycle incomes, the team owners may choose the ticket prices in the inelastic regions of the attendance demand. The team owners are likely to do so if the intertemporal elasticity of substitution in the fans' attendance at sports games (the degree of the fans' willingness to substitute their game attendance in the current time period for the attendance in the future periods in response to an increase in the relative ratio of the future and current ticket prices) is low. In addition to the sports fans' forward-looking consumption decisions the habit-forming nature of the consumption of the sports games can also encourage the inelastic-pricing decisions of the team owners. Attending sports games is likely to be habit-forming. Current season-ticket holders are more likely to buy the season tickets for the next season than non-holders do. Accordingly the team owners may have incentives to trade their current profits for higher future profits by lowering the current ticket prices to boost the current and future attendances. We show that this conjecture is in fact consistent with the maximization problem of a team owner's discounted current and future profits. In our model inelastic-pricing could be a direct outcome of the team owners' efforts to maximize their current and discounted future profits.

Second, we empirically test the habit-forming attendance decisions of MLB fans using a panel data approach. We find strong evidence that the attendance at the MLB games is habit-forming: The future attendance growth is strongly positively related with the past attendance growth. We also find that the intertemporal elasticity of substitution in the MLB attendance is not statistically significant. This result is consistent with the robust findings by many previous studies that the intertemporal substitution effect in the aggregated consumption is statistically insignificant (e.g., Hall, 1988; and Guvenen, 2005).[2]

The foundation of our empirical model is a life-cycle-rational-expectation model of habitual-forming consumption. There have been numerous theoretical and empirical papers that have studied habitual-forming consumption behaviors. Examples are Becker and Murphy (1988), Constantinides (1990), Becker, Grossman and Murphy (1991, 1994), Ferson and Constantinides (1991), Heaton (1995), Fuhrer (2000), and Dynan (2000), amongst others. Our study is closely related to Becker, Grossman and Murphy (1994, hereafter, BGM) and Dynan (2000).

BGM empirically test whether smoking is a habit-forming consumption behavior and whether cigarette consumption decisions are forward-looking (that is, whether smokers make

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[2] Guvenen (2005) finds evidence that the intertemporal elasticity is higher in a small group of wealthy people, while it is low in a majority of other people.

their consumption decisions knowing that their current cigarette consumption can influence their future preferences for smoking). Dynan (2000) tests whether or not individual households' consumptions of food, nondurable goods and services are habitual. While these two studies are related, they are different in two important respects. The model of BGM assumes that consumers have quadratic utility functions and perfect foresight about their future. In contrast, Dynan's model assumes that consumers make their consumption decisions based on their expectations of the future and their utility functions are constant-relative-risk-averse (CRRA). We build the attendance demand for MLB based on Dynan's model.

This paper proceeds as follows. Section 2 presents a theory of inelastic pricing based on life-time profit maximization. Section 3 derives our empirical model for the sports fans' attendance decisions. Section 4 presents our empirical results. Concluding remarks follow in section 5.

2. Profit Maximization When Consumers Are Rational and Habit-forming

In this section we consider a simple two-period model (current and one-period in the future) of a professional baseball team owner and a representative fan. Our results obtained below can be easily generalized to multi-period models. For simplicity we assume that both the owner and the fan have perfect information about the future. Based on the information about the fan' current and future demand curves the owner determines the profit-maximizing current and future price levels. The fan is rational; that is, he decides on his life-time-utility-maximizing current and future attendance levels (ATT_1 and ATT_2) given the current, future ticket prices (p_1 and p_2), and his life-time wealth.

In addition to the assumption that the fan is rational (rationality assumption), following BGM, we assume that the professional baseball games are habit-forming (addictive); that is, as the fan attends more baseball games in the current year, the marginal utility increases that he can obtain by attending an extra game in the future year. We call this "habit" assumption. Under this assumption ATT_2 is positively related to ATT_1 other things being equal.

The rationality and habit assumptions lead us to the following two demand curves:[3]

$$ATT_1 = ATT_1(p_1, p_2); ATT_2 = ATT_2(ATT_1, p_1, p_2), \quad (1)$$

where $\partial ATT_2 / \partial ATT_1 \geq 0$ and $\partial ATT_j / \partial p_j < 0$ for j = 1, 2. The signs of $\partial ATT_2 / \partial p_1$ and $\partial ATT_1 / \partial p_2$ depend on the intertemporal elasticity of substitution (IES) in the fan's attendance at the baseball games, the degree of the fan's willingness to substitute his current consumption of the sports games for his future consumption in response to an increase in the ratio of the future and current ticket prices, as we see below. If the baseball games are not habit-forming, it must be the case that $\partial ATT_2 / \partial ATT_1 = 0$. If the fan is myopic (not

[3] In fact, ATT_1 and ATT_2 also depend on the prices of other goods and the fan's life-time wealth. However, including such variables does not alter our main results.

rational); that is, if the fan's decision on his attendance level at the period j is made based only on the ticket price at the period j (with the ticket prices at other periods ignored), we must have $\partial ATT_1 / \partial p_2 = \partial ATT_2 / \partial p_1 = 0$.

With these two demand curves, the owner solves the following problem:

$$\max_{p_1, p_2} (p_1 - c) ATT_1(p_1, p_2) + \frac{1}{1+r}(p_2 - c) ATT_2(ATT_1, p_1, p_2), \tag{2}$$

where r is the real interest rate, and c is the constant marginal cost.[4] The first-order conditions for the problem (2) immediately imply that at the profit-maximizing prices,

$$\varepsilon_1 = 1 - \frac{c}{ATT_1}\frac{\partial ATT_1}{\partial p_1} + \frac{1}{1+r}\frac{p_2 - c}{ATT_1}\left(\frac{\partial ATT_2}{\partial ATT_1}\frac{\partial ATT_1}{\partial p_1} + \frac{\partial ATT_2}{\partial p_1}\right), \tag{3}$$

where ε_1 is the price elasticity of current demand, and $\partial ATT_2 / \partial p_1$ is the partial derivative obtained holding ATT_1 fixed.[5,6]

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[4] We assume a constant marginal cost of c for simplicity. It does not affect our main results.

[5] In this moment, we assume that the qualities of players or ballpark do not influence the attendance demand. In reality, such qualities will be the important factors determining the attendance demand, so the team owner needs to make the investment decisions on players and ballpark. However, introducing such investment decisions into the profit maximization model (2) would not alter our main result. Suppose that Q (such as # of quality players) is an input needed to attract the fan. To allow the fan's current and future attendance levels to depend on Q, we may assume that $ATT_1 = ATT_1(p_1, p_2, Q)$, and $ATT_2 = ATT_2(ATT_1, p_1, p_2, Q)$ for Equation (1). Here, we assume that the owner uses the same level of Q for both the current and future time periods. We can allow her (the owner) to use the different levels of Q for the two time periods. But this generalization would not change our result. Now, let us use C(Q) to denote the cost function for Q. The introduction of Q into the model (2) does not change the equality in (3), because the equality is derived from the first-order profit maximization condition with respect to p_1 only. The dependence of the attendance and the cost on Q does not play any role in Equation (3).

[6] If we assume that the cost function, say C(ATT), is nonlinear, the two c's in Equation (3) will be replaced by $\partial C(ATT_1) / \partial ATT_1$ and $\partial C(ATT_2) / \partial ATT_2$, respectively.

For comparison, let us use ε_1^o to denote the price elasticity when the fan is myopic and the sports games are not habit-forming ($\partial ATT_2 / \partial ATT_1 = \partial ATT_2 / \partial p_1 = 0$). Then, from (3), we can have:

$$\varepsilon_1^o \equiv 1 - \frac{c}{ATT_1} \frac{\partial ATT_1}{\partial p_1} \geq 1. \qquad (4)$$

This result implies that the team owner always sets the current-year ticket price in the region where the demand curve of the current-year attendance is elastic. Since the marginal costs of serving an extra fan in a huge ballpark or stadium are generally small, it would be reasonable to assume that the size of the marginal cost c in (4) is small. If so, we can expect that the price elasticity of the attendance demand would be close to one if the fan is myopic and the sports games are not habit-forming (addictive).

If the fan is myopic and his attendance at the games is habit-forming, that is, if $\partial ATT_2 / \partial ATT_1 > 0$ and $\partial ATT_2 / \partial p_1 = 0$, then by comparing (3) and (4) we can easily see that $\varepsilon_1 < \varepsilon_1^o$. Thus the addiction assumption decreases the price elasticity. The owner is more likely to set the current-year ticket price in the inelastic region of the attendance demand when the marginal cost c is small and the habit effect is large.[7]

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[7] When a team owner plans to sell her team, she might ponder on increasing the ticket price to earn more profits in the last year of her ownership by capitalizing on the pool of the "addicted" fans she has been accumulated in the past years. However, the increase in the ticket price will shrink the pool for the coming years hurting the team's future profitability. Thus, if a team's market value (which the owner can collect when she sells her team) equals its' life-time profitability, the owner would have no incentive to increase ticket price abruptly even if he/she decides to sell his/her team.

We now consider the case in which the fan is rational and the games he attends are habit-forming (addictive). For this case, the sign of $\partial ATT_2 / \partial p_1$ is an important factor. For example, if $\partial ATT_2 / \partial p_1 < 0$, we clearly have $\varepsilon_1 < \varepsilon_1^0$ from (3) and (4). For this case, both the rationality and habit assumptions contribute to encourage the owner to set p_1 in the inelastic region of the demand curve $ATT_1(p_1, p_2)$. In contrast, if $\partial ATT_2 / \partial p_1 > 0$, the rationality and habit assumptions have the opposite effects on the owner's price decisions. The fan's rationality encourages the owner to set the ticket price in the elastic region, while the habit effect works in the opposite way.

In the above, we have argued that the signs of $\partial ATT_2 / \partial p_1$ and $\partial ATT_1 / \partial p_2$ depend on IES in the baseball attendance. To see why consider a simple two-period model (current and one-period in the future) of the representative fan's attendance decisions. Taking into account his life-time wealth, he determines his consumptions of the baseball games (ATT_1 and ATT_2) and a composite good Y (Y_1 and Y_2). His one-period utility function is separable between ATT and Y. Attending at the baseball games is habit-forming (additive) while the consumption of the composite good Y is not. Following Dynan (2000), we assume that the fan's current and future utility functions are given:

$$U_1(ATT_1, Y_1) = \frac{ATT_1^{1-1/\gamma}}{1-1/\gamma} + \frac{Y_1^{1-1/\gamma}}{1-1/\gamma};$$
$$U_2(ATT_1, ATT_2, Y_2) = \frac{(ATT_2 - \alpha ATT_1)^{1-1/\gamma}}{1-1/\gamma} + \frac{Y_2^{1-1/\gamma}}{1-1/\gamma}, \tag{5}$$

where $\alpha \geq 0$. Here γ is the IES parameter.[8] For simplicity we assume that the IES parameter is the same for both ATT and Y. The baseball games are habit-forming if $\alpha > 0$.

For simplicity we assume that the fan earn zero incomes in any period, but has an initial endowment A. He can rent or borrow money without any constraint at the real interest rate r. His subjective time discount factor is β which, we assume for simplicity, equals 1/(1+r). We assume that the fan has perfect information about the future; that is, there is no uncertainty. Under these assumptions, the fan tries to maximize his life-time utility:

$$U_1(ATT_1, Y_1) + \beta U_2(ATT_1, ATT_2, Y_2) \tag{6}$$

subject to her life-time budget constraint:

$$A = p_1 ATT_1 + q_1 Y_1 + \beta(p_2 ATT_2 + q_2 Y_2) \tag{7}$$

where p and q are the prices of ATT and Y.

A straightforward algebra shows that the utility-maximizing current and future consumption levels of ATT are given:

$$ATT_1^* = \frac{(p_1 + \alpha\beta p_2)^{-\gamma} A}{S}; \quad ATT_2^* = \alpha ATT_1^* + \frac{p_2^{-\gamma} A}{S}, \tag{8}$$

[8] It would be worth noting that γ is not an IES measure in actual attendance levels (ATT_2 and ATT_1). But, if we view ATT_1 and (ATT_2-αATT_1) as the amounts of the current and future consumption services the fan receives by attending the baseball games, we can interpret γ as the IES measure between these consumption services. This is so because the maximization of the fan's life-time expected utility implies that $\gamma = -\partial \ln[(ATT_2 - \alpha ATT_1)/ATT_1]/\partial \ln(p_2/p_1)$.

where $S=(p_1+\alpha\beta p_2)^{1-\gamma}+\beta p_2^{1-\gamma}+q_1^{1-\gamma}+\beta q_2^{1-\gamma}$.[9] From these demand curves we can easily obtain:

$$\frac{\partial ATT_1^*}{\partial p_1}=\frac{-(p_1+\alpha\beta p_2)^{-\gamma-1}[\gamma(\beta p_2^{1-\gamma}+q_1^{1-\gamma}+\beta q_2^{1-r})+(p_1+\alpha\beta p_2)^{1-\gamma}]A}{S^2}<0; \qquad (9.1)$$

$$\left.\frac{\partial ATT_2^*}{\partial p_1}\right|_{ATT_1^*\ fixed}=-\frac{(1-\gamma)(p_1+\alpha\beta p_2)^{-\gamma}p_2^{-\gamma}}{S^2}; \qquad (9.2)$$

While $\partial ATT_1^*/\partial p_1$ is signed, $\partial ATT_2^*/\partial p_1\big|_{ATT_1^*\ fixed}$ is not. However if the IES parameter γ is smaller than unitary we can see that the derivative (9.2) becomes negative. For this case, as we discussed above, the team owner is likely to set the (current-year) ticket price in the inelastic region of the demand curve; that is, inelastic pricing can be consistent with the team owner's profit maximizing decisions. In contrast, if the IES parameter is greater than unitary the derivative (9.2) becomes positive. For this case, the fan's rationality and the habit-forming nature of the baseball games work in the opposite ways; the former encourages the owner to choose an elastic price, while the latter discourages.

Some intuitive explanations follow for the implications of the above simple monopoly pricing model. When the IES parameter is small ($\gamma < 1$), the fan adjusts his current and future consumption levels only slightly in response to an increase in the current ticket price. This small adjustment in attendance leads to a decrease in the fan's real purchasing power of his life-time wealth (income effect). Thus an increase in the current price per baseball game will decrease both the fan's current and future attendances, resulting in smaller expected life-

[9] Positive earnings, if any, will influence his utility-maximizing attendance level through A.

time profits. Thus the team owner has an incentive to lower the current-year ticket price. In contrast, when the IES parameter is large ($\gamma > 1$), the fan will respond by a large scale to a small increase in the current ticket price, increasing their real purchasing power. The fan's attendance demand for the current year will fall but the increase in his future attendance demand will boost the team owner's life-time profits. This motivates the owner to charge a higher price for the current year.

In contrast to the intertemporal substitution effect, the habit effect works in only one direction; an increase in the current-year attendance level will accompany an increase in the future attendance level. Thus the team owner can enhance her future profits by encouraging the fan to attend more games in the current year with a lower price.

So far we have considered a model in which the representative fan has perfect information about the future. While the model provides a useful insight into sports fans' forward-looking demand decisions and team owners' expected future profit maximization problems, the assumption of perfect information remains too restrictive. In the next section we will derive an econometric model relaxing the assumption.

3. Empirical Model

In this section, we consider a rational-expectation and life-cycle consumption model of the MLB games, which we can use to estimate the IES parameter and test whether the MLB games are habit-forming. Becker and Murphy (1988) and BGM have studied the effect of addiction on consumers' consumption decisions in the context of smoking. In particular, BGM provides empirical evidence that smoking is an additive (habitual) consumption behavior, but smokers' smoking decisions are rational and forward-looking.[10] In spirit our model is closely related to their model. But it is also different from their model in two important ways. First, following Dynan (2000), we use the CRRA utility function (5) instead of a quadratic utility. Second, we allow future uncertainty in the model.

Extending the two-period model discussed in the previous section we assume that the representative baseball fan makes a decision on the number of the MLB games he will attend by maximizing his life-time expected utility at time t_o:

$$\max_{ATT_{t_o},\dots,ATT_{t_o+T},Y_{t_o},Y_{t_o+1},\dots,Y_{t_o+T}} E\left(\Sigma_{t=t_o}^{T} \beta^t \exp(X_t'\theta) \left\{ \frac{(ATT_t - \alpha ATT_{t-1})^{1-1/\gamma}}{1-1/\gamma} + v(Y_t) \right\} \middle| \Omega_{t_o} \right) \quad (10)$$

subject to the intertemporal budget constraint:

$$A_t \le (1+r)A_{t-1} + w_t - p_t ATT_t - q_t Y_t. \quad (11)$$

Here, A_t denotes the value of asset at time t, w_t is the earnings at time t, the X_t is a vector of the observable variables that can shift the fan's temporal utility function. The $v(Y_t)$ is the temporal utility function of the consumption goods and services other than the MLB games. The symbol Ω_{t_o} means the information set available to the sports fan at time t_o. The term,

[10] In empirical exercises, we also have estimated the MLB attendance model based on BGM. We do not report the estimation results in this paper, because we did not obtain meaningful results. The results are available upon request from authors.

$ATT_t - \alpha ATT_{t-1}$, is the consumption service flow from the MLB games the fan attend at time t. As in the previous section, we assume that the real interest rate r is constant over time, and that $\beta = 1/(1+r)$.[11] All other notation is defined as in the previous section.

Under the above assumptions, it is straightforward to show that the solution of the problem implies:

$$E\left(\exp(\Delta X_{t+1}{}'\theta) \frac{(ATT_{t+1} - \alpha ATT_t)^{-1/\gamma} / p_{t+1}}{(ATT_t - \alpha ATT_{t-1})^{-1/\gamma} / p_t} \middle| \Omega_t \right) = 1. \quad (12)$$

If we linearize this condition following Dynan (2000), we obtain a regression model:[12]

$$\Delta \ln(ATT_{t+1}) = \alpha \Delta \ln(ATT_t) - \gamma \Delta \ln(p_{t+1}) + \Delta X_{t+1}{}'\theta + \varepsilon_{t+1} \quad (13)$$

where ε_{t+1} is the forecast error. This linearized condition is the foundation of our empirical study.

It is important to notice that the equation (13) is not of a demand curve, although it looks akin to the first-differenced form of a standard demand curve with a one-period lagged attendance as an additional regressor. The equation is merely a utility maximization condition. If one views (13) as a demand curve, she could interpret γ (IES) as the short-run price elasticity. However, as we have seen in the previous section, the short-run price elasticity of demand for MLB depends not only on IES, but also on current and (expected)

[11] Our results do not change even if we allow the discount rate β to be different from $1/(1+r)$.

[12] This approximation requires $-1 < \alpha < 1$. See Dynan (2000). Our empirical result indicates that the consumption of MLB satisfies this restriction.

future ticket prices. An estimated coefficient of $\Delta\ln(p_{t+1})$ should be interpreted as an estimate of IES, not of the price elasticity.

We also note that the estimation of (13) may require use of the instrumental variable method. If the ATT_t were observed without any measurement error the equation can be estimated by usual OLS (Ordinary Least Squares). However the attendance data we use in this paper are likely to suffer from measurement errors. In our data the price variable is the weighted average of the prices for different seats with different qualities. In contrast our attendance measure is the actual number of attendees: one attendee at the third class seat and one at the first class seat are counted with the same weight. Given our price data the adequate measure of attendance must be the level weighted by the numbers of seats with different prices. Accordingly, our attendance variable is a proxy variable of the correct attendance measure involving some measurement errors. This problem induces MA(2) in the error terms ε_{t+1}, and thus the lagged attendance growth rate $\Delta\ln(ATT_t)$ become endogenous: $E[\Delta\ln(ATT_t)\varepsilon_{t+1}] \neq 0$ (see Dynan, 2000).[13] We will address this issue in detail in the next section.

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[13] The attendance data we use may be censored by sell-out games. In a sense, the differences between the actual attendance demand levels and the reported attendance levels (censored by ballpark capacities) could be viewed as measurement errors in attendance data. If so, the potential censoring problem may in fact support our use of GMM. Of course, the GMM estimates would be biased if the degree of censoring in data is very high. In order to control for the potential biases, one may think of using a tobit model as an alternative. But the tobit model may not be appropriate for our study. To use the tobit model, a researcher needs to know the threshold values of the dependent variable at which the variable is censored. However, since our attendance measure is the total number of attendees and not all games are sold out, we are unable to determine the threshold

4. Data and Empirical Results

4.1 Data

The data we analyze consist of the time series of all Major League Baseball (MLB) teams covering the periods from 1969 through 2000. Table 1 contains the sample means and standard deviations of the primary variables in the data set. We obtain the MLB ticket price data from the Professor Fort's Sports Business Data Pages. We also obtain from the US Census Bureau the per capita personal income (INC) and population (POP) of the metropolitan statistical area in which each team is located. The prices and income measures (p and INC) are real terms. The win/loss records of individual teams, WPCT (winning percentage) and GB (number of games back behind the leader of a division), are taken from Baseballstat.net. We also obtain from the same site the dummy variables for each MLB team's post-season performances, POFF (advance to playoff), LCHP (American or National league championship), and WCHP (World Series championship).

There are thirty MLB teams, but among them four teams (Arizona Diamondbacks, Tampa Bay Devil Rays, Montreal Expos, and Toronto Blue Jays) are dropped from our

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value for each team. Quirk and Fort (1992) summarize the sellout (90 percent of capacity or more) game percentages of the four major professional leagues in the States (MLB, NHL, NBA and NFL) for the 1990 season. Their results indicate that MLB has the distinctively least sellout percentage among the four. For instance, the number of the teams with 100 percent sellout games is none in MLB, but is 7, 11, 5 in NHL, NBA and NFL, respectively.

analysis. We drop Arizona and Tampa Bay from our analysis since the two expansion teams do not provide enough information. We also drop the two Canadian teams, Montreal and Toronto, because the fluctuations in the exchange rate between US and Canadian dollars may influence our empirical results when they are included. We use the data from the year of 1969 because of the availability of the city-specific data. The data for the period of 1986-1990 are omitted because the ticket price data are missing for the period. The sample we use includes some expansion teams, such as the Colorado Rockies, which enter MLB after the year of 1969. Thus, our data are unbalanced panel data.

4.2 Empirical Results

Our regression analysis is based on the equation (13). The dependent variable is the attendance growth rate ($\Delta \ln(ATT_{t+1})$). The regressors of our major interest are the lagged attendance growth ($\Delta \ln(ATT_t)$), and the price growth rate ($\Delta \ln(p_{t+1})$). We include into the set of control variables, POP, WPCT, GB, POFF, LCHP, WSCHP, and one categorical variable, NEWBP. The latter variable is designed to capture the effects of newly built or renovated ballparks on the attendance at the MLB games. The effect of new ballpark is likely to decrease over time. In order to capture this aging effect we use a four-year reverse trend; that is, NEWBP is equal to 4 in the first year of a new or renovated ballpark, 3 for the second year, 2 for the third year, and 1 for the fourth year (see Poitras and Hadley (2006)).

In order to control for time-specific fixed effects, we add the time dummy variables to the set of our regressors. We do regressions both with and without the team dummy variables. For the regressions with the team dummy variables we treat unobservable team heterogeneity as fixed, not as random effects.[14] We do so because our sample covers most of the MLB teams in US (except the most recent extension teams).

While the utility shifting variables X_{t+1} enter the equation (13) in differenced forms, in estimation we use both the changes in the team performance measures ($\Delta WCPT_{t+1}$, ΔGB_{t+1}, $\Delta POFF_{t+1}$, $\Delta LCHP_{t+1}$, and $\Delta WSCHP_{t+1}$) and their one-period lagged levels ($WCPT_t$, GB_t, $POFF_t$, $LCHP_t$, and $WSCHP_t$). We do so because, in reality, a team's performances in the last season could have some lagging effects on the attendance growth for the current season. For example, suppose that in this year, two teams, say teams A and B, have improved their winning percentages by exactly the same amount from the winning percentages they earned in the previous year, but team A's winning percentage was greater than that of team B. For this case, the growth rate of attendance at team B's home games would be greater than that at team A's home games, because an improvement in the winning records by the teams that

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[14] Given that our dependent variable is the attendance growth, the coefficients of team dummy variables capture team-specific time trends. The reason why we estimate our model with time-dummy variables is that if the model were misspecified, the coefficients of time-dummy variables would pick up the biases by omitted regressors or endogenous instruments. Our estimation results indicate that there are no team-specific time trends.

performed poorly in the previous season will collect more attentions from their fans that that by the teams with better previous records.

In addition to the performance measures, we also use as the regressors population growth ($\Delta\ln(POP_{t+1})$), the current and lagged changes in NEWBP ($\Delta NEWBP_{t+1}$ and $\Delta NEWBP_t$). Differently from the performance measures, we use $\Delta NEWBP_t$ (lagged change) instead of $NEWBP_t$ (level change) because, in all of the regressions either reported or unreported, the estimated coefficients of $\Delta NEWBP_t$ were robustly significant while those of $NEWBP_t$ are not.[15] In sum, the basic model we estimate is:

$$\begin{aligned}\Delta\ln(ATT_{t+1}) = \alpha\Delta\ln(ATT_t) - \gamma\Delta\ln(p_{t+1}) + \Delta X_{t+1}{}'\theta + Z_t{}'\xi \\ + Team\ effects + Time\ effects + \varepsilon_{t+1}\end{aligned}, \quad (14)$$

where,

$$X_{t+1} = (NEWBK_{t+1}, NEWBK_t, WPCT_{t+1}, LCHP_{t+1}, \ln(POP_{t+1}), GB_{t+1}, POFF_{t+1}, WCHP_{t+1})';$$

$$Z_{t+1} = (WPCT_t, LCHP_t, GB_t, POFF_t, WCHP_t)'.$$

For our regressions, we treat the change in price ($\Delta\ln(p_{t+1})$) and the regressors in X_{t+1} as weakly exogenous with respect to the forecasting error ε_{t+1}: that is, $E[\Delta\ln(p_{t+1})\varepsilon_{t+1}] = 0$ and $E(X_{t+1}'\varepsilon_{t+1}) = 0$. By doing so we are assuming that the MLB teams fix at the beginning of a season admission prices and do not change them during the season. This assumption is reasonable in that the MLB teams sell season tickets before a season starts. We are also

[15] In unreported regressions, we also have used as regressors $NEWBP_t$ and $NEWBP_{t-1}$ instead of $\Delta NEWBP_t$. We failed to reject the hypothesis that the sum of the coefficients of $NEWBP_t$ and $NEWBP_{t-1}$ equals zero, supporting our use of $\Delta NEWBP_t$.

assuming that the MLB fans can foresight individual teams' one-year future performances. This assumption could be justified by the fact that the current and one-season ahead performances of professional sports teams are generally highly correlated.[16] In addition, as shown in Tables 2 and 4, we fail to reject the legitimacy of our exogeneity assumption. Finally, we assume that population growth ($\Delta \ln(POP_{t+1})$) and the change in the quality of a team's ballpark ($\Delta NEWBP_{t+1}$) are exogenous. This assumption can be easily justified.

As the instrumental variables for the lagged attendance growth rate, $\Delta \ln(ATT_t)$, we use the two-year lagged level variables related to team performances and ballpark conditions ($WPCT_{t-1}$, GB_{t-1}, $POFF_{t-1}$, $LCHP_{t-1}$, $WSCHP_{t-1}$, and $NEWBP_{t-1}$), as well as the one- and two-year lagged ticket prices. We use the level instead of differenced instruments, because Arellano (1988) reports that use of lagged level instruments (as well as lagged differenced ones) for differenced endogenous regressors often improves the finite sample properties of instrumental variables estimators. In addition, we use the one-year and two-year lagged per-capita real incomes in log form ($\ln(INC_t)$ and $\ln(INC_{t-1})$). They are legitimate instruments because they should not be correlated with future forecasting errors under the rational expectation assumption.

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[16] In fact, this perfect-foresight assumption is unnecessary as long as we can assume that the forecasting errors for team performances made by fans are uncorrelated with the forecasting errors due to unexpected changes in fans' preferences and (local) economic conditions.

Notice that income variables do not appear in the Euler equation (12).[17] Accordingly, if the equation (14) (or (13)) is a good approximation of (12), the equation should not depend on income variables. Thus we indirectly check the relevance of the linearized Euler condition (14) by testing significance of the income growth rate, $\Delta\ln(INC_{t+1})$, in the regression of (14) using the income variable as a regressor. This variable is likely to be correlated with the forecasting error term ε_{t+1}, if (potential) fans do not have perfect information about their future earnings. Thus we treat $\Delta\ln(INC_{t+1})$ as endogenous in all of the regressions reported.

Table 2 reports the OLS and two-step Generalized Method of Moments estimates (GMM; see Hansen, 1982) obtained controlling for autocorrelations in the errors by the Newey-West method (1987) setting the bandwidth parameter at three.[18] Notice that the regressions reported in the table do not use GB, POFF and WSCHP as regressors. As reported in the appendix (Table A.1), these variables are not significant as regressors. These variables do not provide relevant instruments either. In unreported regressions, the two-year lagged values of the three variables were only weakly correlated with our endogenous regressor, $\Delta\ln(ATT_{t+1})$. Thus, we only report the results obtained from the regressions omitting the three variables.

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[17] Fans' current and past income levels, through their life-time wealth, can influence their current and future consumption levels. However, (12) implies that the expected growth rates of consumption service from attendance do not depend on current and past income levels.

[18] Our results are not sensitive to this choice of bandwidth.

Panel I of Table 2 reports the results from the regressions obtained controlling for both time and team effects, while Panel II reports the results obtained controlling time effects only. The OLS results are reported in the first column of each panel. In the columns headed with GMM (i) and GMM (ii) we present the GMM estimates obtained from the regression without and with $\Delta\ln(INC_{t+1})$ as a regressor, respectively.

The OLS results (in Panel I) indicate that both the coefficients of the lagged attendance growth and the change in ticket price are insignificant: There is no strong evidence supporting the notion that attending the MLB games is habit-forming. The estimated coefficient of the price change is unexpectedly positive although it is statistically insignificant. The two variables, $\Delta NEWBP_{t+1}$ and $\Delta NEWBP_t$ (the current and lagged changes in the quality of ballpark), have significant but opposite effects on the attendance growth. As expected, the current change in the quality of ballpark ($\Delta NEWBP_{t+1}$) increases the current attendance growth rate. But the one-year lagged change ($\Delta NEWBP_t$) rather decreases the attendance growth. It appears that new or renovated ballparks attract the MLB fans mostly in their first years, but they rather slow the attendance growth in the following years. Both higher $\Delta WPCT_{t+1}$ and $WPCT_t$, as well as $\Delta LCHP_{t+1}$ and $LCHP_t$, lead to higher attendance growth. The coefficient of the population growth ($\Delta\ln(POP_{t+1})$) is unexpectedly negative, but it is insignificantly different from zero.

As we have discussed in section 3 the OLS estimates are inconsistent if the attendance data contain measurement errors. The GMM estimation results reported in Table 2 justify this concern. The χ^2-tests for the exogeneity of $\Delta\ln(ATT_t)$ soundly reject the hypothesis that the lagged attendance growth rate is not correlated with the model error terms ε_{t+1}.[19] The Hansen tests (over-identifying restrictions tests) do not reject the legitimacy of our instruments and model specification. These results are supportive for our use of GMM instead of OLS. The model (14) is estimated by GMM assuming that the price change $\Delta\ln(p_{t+1})$ is (weakly) exogenous. We formally test this assumption. Our χ^2-tests do not indicate any evidence that the price change is correlated with the error ε_{t+1}, supporting our exogeneity assumption. The χ^2-tests for the exogeneity of income growth show some evidence that the variable is potentially correlated with model error terms. However the Hansen tests do not reject the model specification (14) whether or not the income growth rate is used as a regressor. Furthermore, the income growth rate is insignificant in the regression regardless of whether individual team effects are controlled. These results provide indirect evidence that the linearized model (14) is a good approximation of the Euler condition (12).

The GMM estimation and test results remain almost identical whether or not individual effects are controlled. In fact, the χ^2 -tests for the equality of team effects reveal no evidence that the effects are different across different MLB teams. Thus, from now on,

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[17] The χ^2-statistics for testing exogeneity of $\Delta\ln(ATT_t)$ and $\Delta\ln(P_{t+1})$ are computed using the GMM method proposed by Eichenbaum, Hansen and Singleton (1988)

we will focus on the results obtained from the regressions with time effects only. The estimated team and time effects are reported in Tables A.2 – A.4 in the appendix.

Compared to the OLS results, the GMM estimation results reveal strong evidence that the consumption of the MLB games is habit-forming (addictive). The coefficient of $\Delta\ln(ATT_t)$ estimated by GMM is 0.641 and its standard error is 0.087 (in the GMM (ii) column of Panel II). This estimated habit-effect is much bigger than the OLS estimate of 0.027 (in the OLS column of Panel II). The GMM estimates of the coefficient of the price change are expectedly negative, but insignificant. Similarly to the case of OLS, this result supports the notion that the intertemporal elasticity of substitution for MLB games is low. The estimated effects of team performances and ballpark-quality by GMM are more or less similar to those by OLS, except that the estimated coefficients of $WPCT_t$ are negative and significant. This result seems to be more intuitive than that from OLS: As we discussed above, the improved performances by the losers of the last season will collect more attentions from the MLB fans than the improvements by the winners of the last season. Population growth appears to have negative effects on attention growth, but they are significant at best 10% of significance level.[20] The population growth does not seem to be an important

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[20] The two GMM columns in Panel II of Table 2 show that the estimated common intercept is positive and statistically significant. Given that we use as the regressors the time dummy variables for the years from 1971 to 2000, we should not interpret the significantly estimated intercept as evidence for a significant time trend. What the intercept really captures is the average attendance growth at the year of 1970, not the average growth over the years from 1971 to 2000.

determinant of the attendance growth. To address further the unexpected sign of the estimated population effects, in unreported regressions we estimated the model (14) excluding the population variable from the lists of regressors and/or instruments. The results were similar to those reported in Table 2. The results are available from the authors upon request.

It is well known that (linear) GMM and instrumental variables estimators could be substantially biased if the endogenous regressors and instruments used are only weakly correlated (See Staiger and Stock, 1997). In order to check the relevance of our instruments, we regress the lagged attendance growth rate ($\Delta\ln(ATT_t)$) on the instruments and the other regressors in (14). The results are reported in Table 3. Overall, the lagged attendance growth rate is highly correlated with the instruments and the other regressors. Furthermore, we soundly reject the hypothesis that conditional on the (weakly) exogenous regressors, the lagged growth rate is uncorrelated with the instruments (see the last row of Table 3). These results indicate that the GMM regression results reported in Table 2 are unlikely to suffer from weak instruments.

We also conduct several sensitivity analyses. First, we reestimate the model (14) using the continuous-updating (C-U) GMM procedure of Hansen, Heaton and Yaron (1996). It has been known that two-step GMM estimators may have poor finite sample properties. C-U GMM estimators have the properties similar to those of the Limited Information

Maximum Likelihood (LIML) estimators for simultaneous equations models. It has been known that the LIML estimators have better finite sample properties than the usual two-stage least squares. Similarly, as Hansen, Heaton and Yaron have shown by a series of simulation exercises, C-U GMM estimators produce more reliable statistical inferences than two-step GMM estimators. Our C-U GMM estimation results are reported in Table 4. The results are materially similar to the results from two-step GMM. The C-U point estimates of the habit effect (the coefficient of the lagged attendance growth) are only slightly greater than those from the two-step estimation. The estimated coefficients of the price change are still insignificant.

Second, we estimate the model (14) with different exogeneity assumptions about the regressors and different sets of instruments. For the regressions reported in Tables 2 and 4, we have assumed that all of the regressors except the lagged attendance growth are weakly exogenous. Although the test results reported in Table 2 support our assumption that the price change is exogenous, we re-estimate the model (14) by two-step GMM treating with the price change treated as endogenous. The results are reported in Panel I of Table 5. Since the estimation and test results are insensitive to whether or not $\Delta\ln(INC_{t+1})$ is used as a regressor, we only report the estimation results obtained without using it. The estimation results are materially similar to those reported in the GMM(i) column of Panel II in Table 2.

Only one noticeable difference from Table 2 is that the estimated price coefficient is now positive. But the coefficient is still statistically insignificant.

Panel II of Table 5 reports the results obtained treating all of the differenced regressors other than $\Delta NEWST_{t+1}$, $\Delta NEWST_t$, and $\Delta \ln(POP_{t+1})$ as endogenous. That is, for the regressions reported in Panel II, all of the performance measures in X_{t+1}, as well as the price change and the lagged attendance growth, are treated as endogenous. In contrast to the results reported in Table 2 and Panel I of Table 5, only two regressors (the lagged attendance growth and the lagged new-ballpark effect) are statistically significant. However, the major results we obtain from Table 2 remain unaltered: Although the estimated coefficient of the lagged attendance growth is smaller than that in Panel I, it is still significant and greater than 0.5. The coefficient of price change is still insignificant.

Panel III of Table 5 reports the GMM results obtained by estimating the same model as Panel II, but excluding lagged income variables from the set of instruments. We conduct this regression because Table 3 indicates that the two lagged income variables ($\ln(INC_t)$ and $\ln(INT_{t-1})$) might be weak instruments. We find no notable difference between the results in Panels II and III. Overall, we do not find that the results of significantly (insignificantly) estimated habit (price) effects are sensitive to the exogeneity assumptions we make for the regressors and instrumental variables we use. We also estimate the models used for Table 5 by C-U GMM, but the estimation and test results remain the same as shown in the appendix (Table A.5).

As a final sensitivity analysis, we estimate the model (14) replacing all of the differenced regressors and dependent variable ($\Delta\ln(p_{t+1})$, ΔX_{t+1} and $\Delta\ln(ATT_{t+1})$) by their level counterparts ($\ln(p_{t+1})$, X_{t+1} and $\ln(ATT_{t+1})$). To estimate this alternative model, we include into X_{t+1} and Z_t the performance measures we have excluded for the analysis of the model (14). The estimation results are reported in Table 6. Not surprisingly, the hypothesis of equal team effects is soundly rejected. The attendance levels of individual teams would depend on many unobservable city-specific characteristics such as fans' royalty to their teams and the weather during the seasons. But the Hansen tests reject the alternative model specification that uses the level attendance and price. This result provides additional supporting evidence for the attendance growth model of (14). It is somewhat interesting to observe that while the level model is rejected, the estimated habit effects appear to be similar to those which are estimated with the model (14). The estimated price effects are still negative and statistically insignificant.

Our estimation results can be summarized as follows. First, we find strong evidence for the habit-forming nature of the MLB attendance. This result is robust to the choice of instruments and estimation method. Second, the estimated intertemporal elasticity of substitution is small and insignificant. This is the result we can expect if the true value of the elasticity is small and close to zero. As we discussed in the previous section, these two results suggest that the MLB team owners would set price tickets in the inelastic demand range. Third, winning percentage and league championship are important factors that influence the fans' attendance decisions. Previous-year performances are also important for the attendance growth. New and renovated ballparks are found to have positive effects on attendance growth, but most of their effects are realized in the first-years. Attendance growth rather slows in the following years. We do not find strong effects on attendance of games back (GB), playoff advance and World Series championships. It appears that winning percentage is a more important determinant of attendance than the intensity of competition in divisions (GB). Among the variables related to teams' postseason games, the league championship is more important for the attendance growth than the advance to playoff and the World Series championship.

5. Conclusion

One robust finding from the many previous studies of the attendance demands for professional sports is that the estimated price elasticity of the demand is smaller than one and/or statistically insignificantly different from zero. Their findings contradict the standard microeconomic theory of a monopolist's profit maximization; in the inelastic range of demand a monopoly firm can raise its profits by reducing its output level. This prediction is based on a one-period model.

In this paper we have shown that inelastic pricing could occur if the team owners attempt to maximize their expected life-time profits instead of one-period profits. Our simple dynamic model predicts that team owners are likely to set inelastic prices if the intertemporal elasticity of substitution in the attendance at sports games is small, and/or if attending the games is habit-forming. Rational fans are aware that their decisions to attend a game could alter their future preferences for the same games. They make their current and future attendance decisions taking into account this habit-forming nature of the sports games as well as the current and future ticket prices. Encountering these rational consumption decisions of the sports fans, the team owners lower ticket prices at the costs of reduced revenues in the current period. However the increased current attendance will result in a greater future attendance raising team owners' future profits.

Based on Dynan (2000), we estimate a linearized Euler condition for sports fans' decisions on their attendance demands for MLB games. Our empirical results provide strong evidence that attending the MLB games is habit-forming. Similarly to many previous studies, we also find that price effects are small and statistically insignificant. This result is consistent with the notion that the intertemporal elasticity of substitution for the MLB attendance is small. Both the strong habit-forming nature of the MLB demand and the small intertemporal elasticity suggest that inelastic pricing would be the outcome of the MLB owners' rational profit-maximizing decisions.

Our model is quite similar to the attendance demand curves that many other previous studies have estimated, except that ours introduces the one-period lagged attendance growth as an additional regressor. However, it is important to note that the coefficient on price in our model is interpreted as the intertemporal preference parameter, not as the price-elasticity of demand. If our multi-period profit maximizing scenario is correct, we can view the demand curves analyzed by previous studies as the Euler conditions for the life-time expected utility maximization of the sports fans with the assumptions that attendances are not habit forming. That is, the price effects estimated by the previous studies are in fact the estimates of the intertemporal elasticity of substitution, not of the price-elasticity of attendance demand. Thus, the empirical results from our study and previous studies are not contradictory. Rather, they are complementary. Both the results suggest that the intertemporal elasticity of substitution for professional sports games is generally small. This low elasticity is not contradictive to the owners' inelastic pricing decisions.

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TABLE 1
Descriptive Statistics for Sample Data

Variable	Mean	Standard Deviation	Maximum	Minimum
ATT: Attendance(millions.)	1.722	0.764	4.483	0.307
P: Real Ticket Price ($)	5.023	3.205	20.618	1.457
INC: Real Income ($ thousands)	11.820	6.987	42.250	2.969
POP: Population (million)	3.959	2.6613	9.547	1.341
NEWBP	0.244	0.833	4.000	0.000
WPCT: Winning Percentage	0.502	0.069	0.704	0.321
GB: Games Back	14.132	11.548	52.000	0.000
WSCHP: WS Championship	0.037	0.188	1	0
LCHP: League Championship	0.075	0.263	1	0
POFF: Playoff	0.185	0.388	1	0

TABLE 2: OLS and Two-Step GMM Estimation

All of the regressors except $\Delta\ln(ATT_t)$ are assumed to be weakly exogenous. The instruments used are the two-year lagged team performance measures and ballpark quality, one-year and two-year lagged price, population and income variables in logarithmic form. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

	Panel I			Panel II		
Variables	Time and Team Effects			Time Effects Only		
	OLS	GMM (i)	GMM(ii)	OLS	GMM (i)	GMM (ii)
$\Delta\ln(ATT_t)$	0.003	0.697**	0.686**	0.027	0.641**	0.634**
	(0.049)	(0.092)	(0.093)	(0.045)	(0.087)	(0.089)
$\Delta\ln(p_{t+1})$	0.122	−0.070	−0.056	0.131	−0.062	−0.058
	(0.122)	(0.129)	(0.133)	(0.119)	(0.122)	(0.126)
$\Delta NEWBP_{t+1}$	0.039**	0.029*	0.031*	0.039**	0.034**	0.034**
	(0.014)	(0.016)	(0.017)	(0.014)	(0.015)	(0.015)
$\Delta NEWBP_t$	-0.016**	-0.050**	-0.055**	-0.017**	-0.050**	-0.050**
	(0.008)	(0.011)	(0.019)	(0.008)	(0.011)	(0.011)
$\Delta WPCT_{t+1}$	1.889**	1.934**	1.926**	1.841**	1.969**	1.964**
	(0.170)	(0.182)	(0.184)	(0.165)	(0.176)	(0.177)
$WPCT_t$	0.420**	-0.544**	-0.521**	0.288**	-0.344**	-0.336**
	(0.150)	(0.173)	(0.172)	(0.135)	(0.133)	(0.135)
$\Delta LCHP_{t+1}$	0.039	0.100**	0.101**	0.037	0.083**	0.083**
	(0.026)	(0.034)	(0.035)	(0.025)	(0.031)	(0.032)
$LCHP_t$	0.091**	0.121**	0.124**	0.083**	0.096**	0.096**
	(0.038)	(0.036)	(0.037)	(0.034)	(0.031)	(0.031)
$\Delta\ln(POP_{t+1})$	-0.139	-0.280*	0.047	-0.113	-0.253*	-0.150
	(0.131)	(0.153)	(0.399)	(0.148)	(0.130)	(0.325)
$\Delta\ln(INC_{t+1})$			-0.951			−0.322
			(1.095)			(0.947)
Constant				-0.117*	0.214**	0.229**
				(0.070)	(0.073)	(0.086)
R^2	0.631	0.430	0.417	0.623	0.450	0.447
Hansen Test$		6.834	6.086		6.915	6.631
		[0.555]	[0.530]		[0.009]	[0.468]
Exogeneity of		48.039			44.797	
$\Delta\ln(ATT_t)$$		[0.000]			[0.000]	
Exogeneity of		1.149			0.417	
$\Delta\ln(P_t)$$		[0.284]			[0.519]	
Exogeneity of		6.074				
$\Delta\ln(INC_{t+1})$$		[0.014]				
Equality of		21.861				
team effects$		[0.644]				

The estimates marked with ** and * are statistically significant at the 5% and 10% significance levels, respectively. The test statistics marked with $ are asymptotically χ^2-distributed under the null hypotheses to be tested. The numbers in (.) are standard errors. The numbers in [.] are p-values.

TABLE 3: Testing the Quality of the Instrument Variables for $\Delta\ln(ATT_t)$

The endogenous regressor $\Delta\ln(ATT_t)$ is regressed on the (weakly) exogenous regressors and the instrumental variables used for the GMM regressions reported in Table 2. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

	Panel I		Panel II	
Variables	Time and Individual Effects		Time Effects Only	
$\Delta\ln(p_{t+1})$	0.128	(0.098)	0.141	(0.098)
$\Delta NEWBP_{t+1}$	0.022	(0.017)	0.017	(0.017)
$\Delta NEWBP_t$	0.060**	(0.015)	0.054**	(0.131)
$\Delta WPCT_{t+1}$	0.007	(0.135)	−0.051	(0.131)
$WPCT_t$	1.985**	(0.198)	1.867**	(0.184)
$\Delta LCHP_{t+1}$	-0.051**	(0.026)	-0.046*	(0.024)
$LCHP_t$	-0.008	(0.034)	-0.001	(0.029)
$\Delta\ln(POP_{t+1})$	0.149	(0.159)	0.247	(0.163)
$\ln(P_t)$	0.109	(0.136)	0.113	(0.130)
$\ln(P_{t-1})$	-0.225	(0.149)	-0.222	(0.143)
$NEWBP_{t-1}$	0.030**	(0.012)	0.023**	(0.011)
$WPCT_{t-1}$	-1.476**	(0.143)	−1.560**	(0.143)
$\ln(INC_t)$	0.664*	(0.384)	0.575	(0.382)
$\ln(INC_{t-1})$	-0.596	(0.411)	-0.549	(0.400)
$LCHP_{t-1}$	0.060**	(0.026)	0.057**	(0.025)
$\ln(POP_t)$	-0.473**	(0.188)	-0.341*	(0.187)
$\ln(POP_{t-1})$	0.365**	(0.185)	0.346*	(0.187)
Constant			−0.393	(0.622)
R^2	0.660		0.643	
F-test for overall significance	25.944	[0.000]	27.465	[0.000]
F-test for significance of instrumental variables	10.822	[0.000]	14.740	[0.000]

The estimates marked with ** and * are statistically significant at the 5% and 10% significance levels, respectively. The test statistics marked with $ are asymptotically χ^2-distributed under the null hypotheses to be tested. The numbers in (.) are standard errors. The numbers in [.] are p-values.

TABLE 4: Continuous-Updating GMM Estimation

All of the regressors except $\Delta\ln(ATT_t)$ are assumed to be weakly exogenous. The instruments used are the two-year lagged team performance measures and ballpark quality, one-year and two-year lagged price, population and income variables in logarithmic form. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

Variables	Panel I: Time and Individual effects GMM (i)	Panel I: Time and Individual effects GMM (ii)	Panel II: Time Effects only GMM (i)	Panel II: Time Effects only GMM (ii)
$\Delta\ln(ATT_t)$	0.722**	0.707**	0.658**	0.648**
	(0.095)	(0.094)	(0.087)	(0.088)
$\Delta\ln(p_{t+1})$	−0.072	−0.053	−0.068	−0.063
	(0.131)	(0.134)	(0.122)	(0.125)
$\Delta NEWBP_{t+1}$	0.030*	0.031*	0.033**	0.033**
	(0.017)	(0.017)	(0.015)	(0.015)
$\Delta NEWBP_{t-1}$	-0.057**	-0.056**	-0.051**	-0.051**
	(0.012)	(0.012)	(0.011)	(0.011)
$\Delta WPCT_{t+1}$	1.933**	1.918**	1.973**	1.965**
	(0.185)	(0.185)	(0.178)	(0.178)
$WPCT_t$	-0.578**	-0.546**	-0.361**	-0.351**
	(0.178)	(0.176)	(0.134)	(0.136)
$\Delta LCHP_{t+1}$	0.102**	0.102**	0.084**	0.083**
	(0.035)	(0.035)	(0.032)	(0.032)
$LCHP_t$	0.121**	0.125**	0.094**	0.094**
	(0.035)	(0.037)	(0.030)	(0.031)
$\Delta\ln(POP_{t+1})$	-0.288*	0.050	-0.262**	-0.155
	(0.153)	(0.401)	(0.131)	(0.326)
$\Delta\ln(INC_{t+1})$		−0.987		−0.336
		(1.111)		(0.949)
Constant			0.220**	0.235**
			(0.073)	(0.086)
R^2	0.398	0.398	0.433	0.436
Hansen Test$		5.835	6.487	9.424
		[0.559]	[0.593]	[0.491]

The estimates marked with ** and * are statistically significant at the 5% and 10% significance levels, respectively. The test statistics marked with $ are asymptotically χ^2-distributed under the null hypotheses to be tested. The numbers in (.) are standard errors. The numbers in [.] are p-values.

TABLE 5: Two-Step GMM Estimation with Different Sets of Instruments

For Panel I, the parameters are estimated assuming that both $\Delta\ln(ATT_t)$ and $\Delta\ln(p_{t+1})$ are endogenous. For Panel II, all of the changes in performance-related regressors, as well as $\Delta\ln(ATT_t)$ and $\Delta\ln(p_{t+1})$, are treated as endogenous. The results reported in Panel III are obtained by GMM assuming all of the performance-related regressors, $\Delta\ln(ATT_t)$, and $\Delta\ln(p_{t+1})$ are endogenous. Income variables are excluded from the set of instruments. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

	Panel I	Panel II	Panel III
Variable	GMM	GMM	GMM
$\Delta\ln(ATT_t)$	0.616**	0.526**	0.553**
	(0.093)	(0.128)	(0.145)
$\Delta\ln(p_{t+1})$	0.104	0.298	0.190
	(0.285)	(0.376)	(0.441)
$\Delta NEWBP_{t+1}$	0.030*	0.021	0.025
	(0.017)	(0.023)	(0.027)
$\Delta NEWBP_t$	-0.051**	-0.050**	-0.053**
	(0.011)	(0.017)	(0.021)
$\Delta WPCT_{t+1}$	1.933**	1.165	1.136
	(0.183)	(0.867)	(1.130)
$WPCT_t$	-0.372**	-0.790	-0.904
	(0.142)	(0.657)	(0.940)
$\Delta LCHP_{t+1}$	0.087**	0.156	0.250
	(0.032)	(0.250)	(0.398)
$LCHP_t$	0.102**	0.183	0.274
	(0.033)	(0.244)	(0.381)
$\Delta\ln(POP_{t+1})$	-0.321*	-0.302	-0.233
	(0.170)	(0.207)	(0.268)
Constant	0.222**	0.410	0.463
	(0.074)	(0.295)	(0.427)
R^2	0.459	0.409	0.336
Hansen Test$	6.341	3.943	2.718
	[0.501]	[0.558]	[0.437]
Exogeneity of $\Delta\ln(ATT_t)$$	39.658	5.151	2.817
	[0.000]	[0.023]	[0.093]

The estimates marked with ** and * are statistically significant at the 5% and 10% significance levels, respectively. The test statistics marked with $ are asymptotically χ^2-distributed under the null hypotheses to be tested. The numbers in (.) are standard errors. The numbers in [.] are p-values.

TABLE 6: OLS and Two-Step GMM Estimation with Level Variables

All of the regressors except ln(ATT_t) are assumed to be weakly exogenous. The instruments used are the two-year lagged team performance measures and stadium quality, one-year and two-year lagged price, population and income variables in logarithmic form. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

Variables	Panel I			Panel II		
	Time and Team Effects			Time Effects Only		
	OLS	GMM (i)	GMM(ii)	OLS	GMM (i)	GMM (ii)
ln(ATT_t)	0.605**	0.528**	0.525**	0.742**	0.579**	0.581**
	(0.036)	(0.070)	(0.071)	(0.030)	(0.063)	(0.064)
ln(p_{t+1})	-0.045	−0.032	−0.035	-0.065	−0.076	−0.074
	(0.056)	(0.070)	(0.072)	(0.045)	(0.057)	(0.060)
$NEWBP_{t+1}$	0.057**	0.051**	0.053**	0.056**	0.049**	0.048**
	(0.011)	(0.008)	(0.010)	(0.013)	(0.011)	(0.013)
$NEWBP_t$	-0.018*	-0.019*	-0.020*	-0.026**	-0.023**	-0.022**
	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)
$WPCT_{t+1}$	1.631**	1.585**	1.587**	1.666**	1.642**	1.644**
	(0.257)	(0.246)	(0.246)	(0.254)	(0.251)	(0.252)
$WPCT_t$	-0.344	-0.298	-0.286	-0.682**	-0.225	-0.235
	(0.219)	(0.246)	(0.258)	(0.227)	(0.262)	(0.272)
$LCHP_{t+1}$	-0.009	-0.001	-0.001	0.013	0.016	0.016
	(0.028)	(0.027)	(0.027)	(0.030)	(0.030)	(0.030)
$LCHP_t$	0.013	0.024	0.024	0.034	0.041	0.041
	(0.031)	(0.031)	(0.031)	(0.033)	(0.035)	(0.035)
ln(POP_{t+1})	-0.094	-0.036	-0.033	0.043**	0.071**	0.070**
	(0.069)	(0.084)	(0.084)	(0.011)	(0.017)	(0.018)
GB_{t+1}	-0.003*	-0.003**	-0.003**	-0.002	-0.003**	-0.003**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
GB_t	0.000	-0.001	-0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
$POFF_{t+1}$	0.037	0.030	0.030	0.032	0.031	0.030
	(0.024)	(0.023)	(0.023)	(0.026)	(0.026)	(0.026)
$POFF_t$	0.047**	0.048**	0.048**	0.029	0.047**	0.047**
	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)	(0.023)
$WSCHP_{t+1}$	-0.003	-0.004	-0.005	-0.032	-0.060	-0.060
	(0.036)	(0.039)	(0.039)	(0.039)	(0.049)	(0.049)
$WSCHP_t$	0.021	0.033	0.032	-0.014	-0.017	-0.018
	(0.037)	(0.038)	(0.038)	(0.040)	(0.048)	(0.048)
ln(INC_{t+1})			0.182			−0.041
			(0.314)			(0.365)
Constant				2.689**	4.439**	4.432**
				(0.425)	(0.701)	(0.702)
R^2	0.900	0.893	0.893	0.885	0.865	0.865
Hansen Test$		22.514	22.637		23.496	23.491
		[0.021]	[0.012]		[0.015]	[0.009]
Equality of team effects$		66.112				
		[0.000]				

The estimates marked with ** and * are statistically significant at the 5% and 10% significance levels, respectively. The test statistics marked with $ are asymptotically χ^2-distributed under the null hypotheses to be tested. The numbers in (.) are standard errors. The numbers in [.] are p-values.

APPENDIX

TABLE A.1
OLS and Two-Step GMM Estimation

All of the regressors except $\Delta\ln(ATT_t)$ are assumed to be weakly exogenous. The instruments used are the two-year lagged team performance measures and ballpark quality, one-year and two-year lagged prices, population and the income variables in logarithmic form. All of the performance variables including GB, POFF and WSCHP are used as regressors and instruments. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

	Panel I			Panel II		
Variables	Time and Team Effects			Time Effects Only		
	OLS	GMM (i)	GMM(ii)	OLS	GMM (i)	GMM (ii)
$\Delta\ln(ATT_t)$	0.004	0.673**	0.664**	0.027	0.630**	0.619**
	(0.049)	(0.086)	(0.086)	(0.044)	(0.083)	(0.084)
$\Delta\ln(p_{t+1})$	0.118	−0.047	−0.026	0.129	−0.051	−0.039
	(0.121)	(0.126)	(0.131)	(1.087)	(0.120)	(0.125)
$\Delta NEWBP_{t+1}$	0.041**	0.031*	0.033**	0.040**	0.035**	0.035**
	(0.014)	(0.016)	(0.016)	(0.014)	(0.015)	(0.015)
$\Delta NEWBP_t$	-0.014*	-0.053**	-0.053**	-0.016**	-0.049**	-0.048**
	(0.008)	(0.011)	(0.011)	(0.008)	(0.010)	(0.010)
$\Delta WPCT_{t+1}$	1.682**	1.747**	1.771**	1.572**	1.696**	1.697**
	(0.296)	(0.331)	(0.340)	(0.275)	(0.308)	(0.311)
$WPCT_t$	0.403	-0.395	-0.357	0.164	-0.287	-0.268
	(0.293)	(0.287)	(0.289)	(0.245)	(0.227)	(0.229)
$\Delta LCHP_{t+1}$	0.014	0.113**	0.109**	0.018	0.088**	0.085**
	(0.037)	(0.043)	(0.044)	(0.037)	(0.041)	(0.042)
$LCHP_t$	0.050	0.138**	0.029**	0.053	0.103**	0.095**
	(0.049)	(0.050)	(0.034)	(0.049)	(0.044)	(0.046)
$\Delta\ln(POP_{t+1})$	-0.111	-0.264*	0.119	-0.102	-0.241*	-0.014
	(0.132)	(0.156)	(0.380)	(0.150)	(0.132)	(0.314)
ΔGB_{t+1}	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GB_t	0.001	0.001	0.001	-0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
$\Delta POFF_{t+1}$	0.029	0.019	0.024	0.035	0.026	0.029
	(0.027)	(0.031)	(0.032)	(0.027)	(0.029)	(0.030)
$POFF_t$	0.042	0.020	0.029	0.049	0.023	0.029
	(0.031)	(0.032)	(0.034)	(0.032)	(0.031)	(0.032)
$\Delta WSCHP_{t+1}$	0.009	-0.068	-0.070	-0.007	-0.057	-0.058
	(0.042)	(0.053)	(0.055)	(0.040)	(0.050)	(0.051)
$WSCHP_t$	0.024	-0.063	-0.057	-0.007	-0.047	-0.041
	(0.059)	(0.053)	(0.056)	(0.052)	(0.046)	(0.048)
$\Delta\ln(INC_{t+1})$			-1.122			-0.711
			(1.030)			(0.902)
Constant				-0.055	0.178	0.211
				(0.145)	(0.136)	(0.144)
R^2	0.633	0.440	0.421	0.625	0.457	0.451
Hansen Test$		10.172	8.986		8.633	8.096
		[0.515]	[0.533]		[0.656]	[0.619]
Equality of team effects$		19.395				
		[0.778]				

The estimates marked with ** and * are statistically significant at the 5% and 10% significance levels, respectively. The test statistics marked with $ are asymptotically χ^2-distributed under the null hypotheses to be tested. The numbers in (.) are standard errors. The numbers in [.] are p-values.

TABLE A.2

Time Effects Estimates from Regressions with Both Time and Team Effects

The table below is a companion with Table 2. These estimates are obtained from the regression reported in the GMM (i) column of Panel I. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

Year	Two-Step GMM		OLS	
	estimates	t-values	estimates	t-values
71	-0.069	-1.155	-0.033	-0.670
72	-0.123	-2.527	-0.123	-2.710
73	0.142	2.806	0.093	1.960
74	-0.134	-2.237	-0.032	-0.529
75	-0.067	-1.138	-0.052	-1.200
76	0.010	0.155	-0.008	-0.169
77	0.025	0.459	0.054	1.167
78	-0.058	-1.001	0.000	0.003
79	-0.024	-0.432	0.018	0.392
80	-0.077	-1.192	-0.027	-0.483
81	-0.520	-11.050	-0.556	-9.899
82	0.831	11.050	0.524	9.703
83	-0.409	-6.775	-0.045	-0.815
84	-0.039	-0.620	-0.043	-0.898
93	0.112	2.471	0.089	2.017
94	-0.499	-9.700	-0.406	-9.014
95	0.193	3.077	-0.040	-0.835
96	0.177	3.707	0.162	3.836
97	-0.125	-2.735	0.008	0.180
98	-0.033	-0.663	-0.013	-0.290
99	-0.020	-0.485	-0.013	-0.330
2000	-0.054	-1.094	-0.042	-0.964

TABLE A.3
Team Effects Estimates from Regressions with Both Time and Team Effects

The table below is a companion with Table 2. These estimates are obtained from the regression reported in the GMM (i) column of Panel I. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

Team	Two-Step GMM		OLS	
	estimates	t-values	estimates	t-values
ANAHEIM	0.206	1.272	-0.157	0.167
BALTIMORE	0.264	1.507	-0.185	0.177
BOSTON	0.238	1.368	-0.216	0.175
CHICAGO (W)	0.211	1.220	-0.175	0.177
CLEVELAND	0.201	1.177	-0.170	0.177
DETROIT	0.214	1.269	-0.172	0.174
KC	0.228	1.369	-0.181	0.171
MILWAWKEE	0.187	1.085	-0.169	0.177
MINNIAPOLIS	0.212	1.247	-0.189	0.173
NEW YORK (Y)	0.226	1.322	-0.214	0.176
OAKLAND	0.222	1.356	-0.197	0.166
SEATTLE	0.235	1.454	-0.160	0.164
TEXAS	0.218	1.329	-0.164	0.168
ATLANTA	0.214	1.233	-0.207	0.180
CHICAGO (C)	0.227	1.396	-0.155	0.167
CINCINNETI	0.232	1.342	-0.215	0.176
COLORADO	0.180	1.051	-0.253	0.171
FLORIDA	0.105	0.588	-0.327	0.184
HOUSTON	0.243	1.441	-0.174	0.174
LOS ANGELES	0.218	1.292	-0.209	0.172
NEW YORK (M)	0.194	1.162	-0.192	0.174
PHILADELPHIA	0.192	1.133	-0.179	0.185
PITTSBERG	0.238	1.409	-0.212	0.172
SAINT LOUIS	0.212	1.287	-0.187	0.169
SAN DIEGO	0.192	1.167	-0.125	0.168
SAN FRANCISCO	0.233	1.377	-0.171	0.172

TABLE A.4

Time Effects Estimates from Regressions with Time Effects only

The table below is a companion with Table 2. These estimates are obtained from the regression reported in the GMM (i) column of Panel II. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

	Two-Step GMM		OLS	
Year	estimates	t-values	estimates	t-values
71	-0.057	-0.924	-0.026	-0.543
72	-0.126	-2.552	-0.114	-2.541
73	0.148	2.810	0.103	2.265
74	-0.131	-2.150	-0.031	-0.528
75	-0.077	-1.286	-0.056	-1.276
76	0.007	0.113	-0.001	-0.024
77	0.025	0.473	0.056	1.242
78	-0.047	-0.822	0.010	0.195
79	-0.024	-0.428	0.021	0.462
80	-0.070	-1.095	-0.026	-0.464
81	-0.532	-10.898	-0.547	-10.232
82	0.815	11.119	0.536	10.332
83	-0.393	-6.601	-0.058	-1.058
84	-0.041	-0.648	-0.037	-0.751
93	0.118	2.634	0.093	2.175
94	-0.481	-9.603	-0.399	-9.164
95	0.158	2.560	-0.042	-0.932
96	0.177	3.761	0.168	4.018
97	-0.119	-2.694	0.006	0.146
98	-0.047	-1.000	-0.022	-0.544
99	-0.016	-0.360	-0.011	-0.267
2000	-0.039	-0.795	-0.117	-0.805

TABLE A.5

C-U GMM Estimation with Different Sets of Instruments

For Panel I, parameters are estimated assuming that both $\Delta\ln(ATT_t)$ and $\Delta\ln(p_{t+1})$ are endogenous. For Panel II, all of the performance-related regressors, as well as $\Delta\ln(ATT_t)$ and $\Delta\ln(p_{t+1})$, are treated as endogenous. The results reported in Panel III are obtained by GMM assuming all of the performance-related regressors, $\Delta\ln(ATT_t)$ and $\Delta\ln(p_{t+1})$ are endogenous. Income variables are excluded from the set of instruments. Standard errors are computed adjusting autocorrelation and heteroskedasticity.

	Panel I	Panel II	Panel III
Variable	GMM	GMM	GMM
$\Delta\ln(ATT_t)$	0.624**	0.578**	0.697**
	(0.093)	(0.121)	(0.181)
$\Delta\ln(p_{t+1})$	0.132	0.315	0.087
	(0.284)	(0.350)	(0.532)
$\Delta NEWBP_{t+1}$	0.029*	0.024	0.039
	(0.017)	(0.021)	(0.031)
$\Delta NEWBP_t$	-0.052**	-0.064**	-0.087**
	(0.011)	(0.017)	(0.030)
$\Delta WPCT_{t+1}$	1.928**	1.015	0.646
	(0.183)	(0.753)	(1.230)
$WPCT_t$	-0.387**	-1.102*	-1.881*
	(0.143)	(0.603)	(1.090)
$\Delta LCHP_{t+1}$	0.088**	0.326	0.848
	(0.033)	(0.244)	(0.518)
$LCHP_t$	0.101**	0.340	0.834*
	(0.033)	(0.236)	(0.493)
$\Delta\ln(POP_{t+1})$	-0.343**	-0.275	-0.049
	(0.168)	(0.197)	(0.360)
Constant	0.227**	0.552**	0.900*
	(0.074)	(0.272)	(0.494)
R^2	0.450	0.408	-0.026
Hansen Test$	6.110	5.237	3.401
	[0.527]	[0.388]	[0.334]

The estimates marked with ** and * are statistically significant at the 5% and 10% significance levels, respectively. The test statistics marked with $ are asymptotically χ^2-distributed under the null hypotheses to be tested. The numbers in (.) are standard errors. The numbers in [.] are p-values.